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Abstract

We explored application of analytical inverse optimization (ANIO) method to the normal finger forces in unimanual and bimanual prehensile tasks with discrete and continuously changing constraints. The subjects held an instrumented handle vertically with one or two hands. The external torque and grip force changed across trials or within a trial continuously. Principal component analysis showed similar percentages of variance accounted for by the first two principal components across tasks and conditions. Compared to unimanual tasks, bimanual tasks showed significantly more frequent inability to find a cost function leading to a stable solution. In cases of stable solutions, similar second-order polynomials were computed as cost functions across tasks and condition. The bimanual tasks, however, showed significantly worse goodness-of-fit index values. We show that ANIO can be used in tasks with slowly changing constraints making it an attractive tool to study optimality of performance in special populations. We also show that ANIO can fail in multi-finger tasks, likely due to irreproducible behavior across trials, more likely to happen in bimanual tasks compared to unimanual tasks.

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INTRODUCTION

The problem of motor redundancy has been one of the central problems in motor control for decades (Bernstein 1967; Turvey 1990). Two main approaches have been developed to deal with this problem. The first approach assumes that the central nervous system (CNS) generates solutions that optimize (maximize or minimize) a particular cost function (Prilutsky and Zatsiorsky 2002). The alternative approach is based on the principle of abundance (Gelfand and Latash 1998; Latash 2012). It assumes that no single solution is generated for a typical task involving multiple effectors but multiple solutions are facilitated equally able to solve the task reflecting the task-specific stability of the action (Schöner 1995). The two approaches look incompatible: a single solution vs. a family of solutions. A recent study has suggested, however, that the two approaches are not mutually exclusive: The former defines an average across trials sharing pattern among elemental variables while the latter is reflected in the structure of inter-trial variance (Park et al. 2011).

Typical optimization approaches to the redundancy problem have used cost functions selected rather arbitrarily, based on intuition of the researchers and/or on reasonable considerations. Examples of such cost functions include minimal time, minimal fatigue, minimal energy, minimal discomfort, minimal jerk-related function, minimal torque-change, and so on (Nelson 1973; Crowninshield and Brand 1981; Hogan 1984; Flash and Hogan 1985; Cruse and Brower 1987; Uno et al. 1989; Rosenbaum 1995; Alexander 2002). Recently, a method of identifying a cost function based on experimental observations has been suggested called *analytical inverse optimization* (ANIO; Terekhov et al. 2010). The method has been applied successfully to multi-finger pressing and prehensile tasks (Park et al. 2010; Niu et al. 2012a,b; Martin et al. 2013). It has shown sensitivity of the cost function and goodness-of-fit index to fatigue (Park et al. 2012), age (Park et al. 2011), and neurological disorder (Parkinson's disease, Park et al. 2013). Negative results were also obtained. The method showed that that an entire large family of cost functions (so-called, additive cost functions, defined below) cannot explain the behavior in the task of force vector production by a multi-joint limb (Xu et al. 2012).

So far, applications of this method have been limited because it required numerous trials by subjects to obtain enough data points spanning wide enough ranges of task constraints. One of the goals of the current study has been to test whether using slowly changing task constraints

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within a trial could be used to obtain multiple data points necessary for ANIO. This could potentially make the method applicable in clinical studies with patients who cannot be expected to perform numerous trials. So, our first hypothesis was that using discrete trials with fixed constraints (as in all earlier studies) and trials with continuously changing constraints would be equally capable of producing data sets for ANIO.

The second goal was to explore whether similar cost functions could be used in unimanual and bimanual prehensile tasks. A number of recent studies of two-hand actions reported significant differences between the control of one-hand and two-hand tasks (Gorniak et al. 2009; Wong et al. 2014). This could be related to differences in the involvement of the two large hemispheres in such tasks (Le and Niemeier 2013; Noble et al. 2014). In particular, Wong et al. (2014) have suggested that two-limb trials are controlled using proprioceptive signals from the limb with the best proprioceptive acuity while the other hand follows. This makes the two hands unequal in two-hand tasks (cf. also the dynamic dominance hypothesis, Sainburg 2005). This allowed us to hypothesize that two-hand prehensile tasks would be less successful in reconstructing cost functions with ANIO compared to similar one-hand tasks (Hypothesis 2).

Static prehensile tasks were used to address the two hypotheses. We used two metrics to test the first hypothesis on the similarity of the discrete and continuous trials: (1) An index of data planarity (the percentage of variance accounted for by the first two principal components); and (2) A goodness-of-fit index, the dihedral angle (D-angle) between the actual data set and the "optimal" data based on the reconstructed cost function with the same task constraints. The second hypothesis – on differences between the one-hand and two-hand tasks – was tested using two indices. The first one was the number of cases when ANIO failed (was unable to reconstruct a cost function with a stable solution), while the second one was the D-angle.

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Methods

Subjects

Nine healthy male subjects (age 26 ± 1.54 years, mass 78.75 ± 4.77 kg, height 176.26 ± 2.52 cm, hand length 19.11 ± 0.28 and 18.63 ± 0.31 m, and hand width 9.05 ± 0.12 and 8.84 ± 0.05 m for the right and left hands, respectively) voluntarily participated in the study. During pilot trials, we tested female subjects and realized that the high handle weight led to fatigue. We could not reduce the handle weight because of the multiple sensors and the attached motor (see below). Therefore we recruited male subjects only for the actual study. The subjects had no history of neuropathy or upper-limb trauma. All subjects gave informed consent according to the procedures approved by the Office of Research Protections of The Pennsylvania State University.

Equipment

Five six-component force/moment transducers (Nano-17 ATI Industrial Automation, Garner, North Carolina, USA) were mounted on an aluminum handle. Four transducers were mounted on one side while the fifth one plus two aluminum pieces of the same shape and size as the transducers were mounted on the other side of the handle (Figure 1A). The transducers measured three components of the digit-tip force vector and three components of the digit moment vector. For unimanual tasks, all five digits were placed on the five force sensors (Figure 1B). In contrast, for the bimanual task, the index and ring fingers of the two hands were placed on the force sensors, while the thumbs of the two hands were placed on the aluminum pieces as shown in Figure 1C. All the transducers and aluminum pieces were covered with sandpaper with the friction coefficient of 1.4-1.5 (Savescu et al. 2008).

<FIGURE 1 ABOUT HERE>

Subjects held an instrumented aluminum handle vertically at all times. A bull's-eye level placed on the top of the handle provided feedback regarding the vertical orientation of the handle, while the required grip force (F_G, defined as the sum of the normal finger forces) time profiles were shown on a computer monitor. Visual feedback on actual F_G was also displayed on the computer monitor as a trace moving from left to right with time (Figure 1). Subjects were asked

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to match the generated and the prescribed F_G profiles. The monitor was placed 0.7 m in front of the subject, at the eye level.

A horizontal inverted-T-shaped slot and slider mechanism was attached to the bottom of the handle (Figure 1A). Different weights could be suspended from the slider. A lightweight motor mounted on the handle moved the slider with the attached weight along the slot via a pulley arrangement over a total distance of 0.5 m, thus allowing the external pronation-supination moment to be varied continuously. The external moment could also be varied in a discrete manner by suspending weights at specific distances from the handle center.

Thirty analog signals from the sensors (5 sensors × 6 components) were routed to a 12-bit analog–digital converter (PCI-6031, National Instruments, Austin, TX). A customized LabVIEW program was used for data acquisition at 100 Hz and subject feedback. MATLAB programs were written for data analysis.

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Experimental procedure

The subject sat comfortably on a stool (no back support), and rested the forearms on supports at a comfortable height. For the unimanual task, the right elbow was flexed at 90°, and the shoulder was abducted at about 45°. For the bimanual task, the left hand mirrored the right hand. Both shoulders were flexed symmetrically such that the fingertips of both hands were comfortably positioned to hold the handle aligned with the mid-line of the body (See Figure 1C; a typical finger configuration is shown in Figure 1D).

The subjects performed three different tasks. The order of tasks was randomized across subjects. In all tasks, subjects were provided feedback on F_G on the computer screen (Figure 2) in addition to the feedback on the handle orientation (via the bull's-eye level). Data collection took two sessions, and each session lasted about 1 hour and 20 minutes. In all trials, the subjects were instructed to hold the handle vertically using one of two possible hand conditions: all digits of the right hand or the index and middle fingers and thumbs of both hands, with the right hand on top. The external conditions were manipulated in various trials by changing the suspended weight (external load, W_{EXT}) and its location (external moment, M_{EXT}). For the unimanual condition, the highest supination moment (negative moment direction) was applied when the weight was at the extreme right position, and the highest pronation moment (positive moment direction) was applied when the weight was at the extreme left position.

<FIGURE 2 ABOUT HERE>

Each experiment began with *practice trials*, in which subjects performed the various tasks (see below) to get acquainted with the tasks and the equipment. No data were recorded during these practice trials. The *baseline trials* were performed next for each W_{EXT} and hand conditions without feedback on F_G. In these trials subjects were asked to hold the handle vertically in a natural way with minimal effort while the weight moved from one side of the T-attachment to the other side. No explicit grip force constraint was specified. The trial began with the subject holding the handle comfortably in the vertical orientation with the external weight in either the extreme left or the extreme right position along the slot. This process was executed in both directions (pronation-to-supination and vice versa). The subject was instructed to hold the handle with minimal effort. The maximal F_G across the two extreme weight locations (F_{GM}) was measured and used for setting F_G profiles in future tasks.

Task 1 used the traditional method of data collection employed in earlier ANIO studies (Niu et al. 2012a,b; Martin et al. 2013). The prescribed F_G and M_{EXT} were both changed discretely across trials. That is, for each trial, the subject maintained a constant, prescribed F_G, and resisted a constant M_{EXT} while holding the handle vertical. Nine grip-force levels (F_{GM} to $1.8 \times F_{GM}$ in steps of 0.1), two W_{EXT} (50 g and 120 g) and five M_{EXT} for each weight (±0.098, ±0.049, 0 Nm, and ±0.24, ±0.12, and 0 Nm, for the 50-g and 120-g W_{EXT}, respectively) were used. To produce a desired M_{EXT}, W_{EXT} was placed at ±20 cm, ±10 cm, and zero distance from the handle central line. At the beginning of each trial, the experimenter took the handle from the subject and held it in a vertical orientation without touching the sensors; the value for all the variables measured by the sensors were set to zero (sensor biasing).

The subject then picked up the handle with the specified hand condition and stabilized the handle in the vertical orientation. Once the handle was stationary, the experimenter began data collection. A target F_G level was shown on the computer screen together with the actual F_G (Figure 2A). The subject had up to 2 s (shown as a vertical line on the screen) to reach the target F_G. Each trial lasted 6 s, and each subject performed 180 trials (9 grip forces × 5 moments × 2 hand conditions × 2 weights). The trials were block randomized for hand condition and W_{EXT}, while F_G and M_{EXT} were fully randomized within each block.

During **Task 2,** subjects varied F_G continuously, while W_{EXT} and M_{EXT} remained fixed within each trial and were changed from trial to trial. Each task began similar to Task 1. After the subject stabilized the handle in the vertical orientation, data collection was started, and the prescribed F_G time profile was displayed on the computer screen as a linear ramp (Figure 2B). The subject had 3 s to match the initial constant F_G (set at F_{GM}), and then followed the ramp by increasing F_G till it reached $1.8F_{GM}$ over 10 s. Each trial lasted 14 s. Subjects performed 20 trials (5 M_{EXT} × 2 hand conditions × 2 W_{EXT}). The trials were block randomized for hand condition and W_{EXT}, but fully randomized for M_{EXT} within each block.

In **Task 3**, M_{EXT} varied continuously as the motor moved the weight along the slot. The weight was moved in both directions (in separate trials): pronation to supination and vice-versa. There were three prescribed constant grip forces $1.25F_{GM}$, $1.5F_{GM}$, and $1.75F_{GM}$. The W_{EXT} speed was 1 cm/s, and M_{EXT} varied from 0.098 Nm to –0.083 Nm for the 50 g weight and from 0.24 Nm to –0.2 Nm for the 120 g weight. Subjects performed 24 trials for Task 3 (3 prescribed F_G × 2 directions of weight movement × 2 hand conditions × 2 W_{EXT}). The asymmetry in the moment values was due to the hardware arrangement.

A 15-s break was enforced after each trial to avoid fatigue. Subjects were also required to ask for rest if they felt tired. A 5-min break was enforced after each task. Several subjects asked for extra rest during the experiment. However, none of the subjects reported feeling fatigued after data collection.

Data processing

MATLAB programs were written for data analysis. The finger forces were low-pass filtered at 5 Hz using a zero lag, fourth-order Butterworth filter. For Task 1, the filtered finger force data from each 6-s trial were averaged over the 2.5–5.5 s window. For Task 2 and Task 3, the appropriate time intervals within the finger-force time series were determined during the F_G ramp increase (Task 2), and M_{EXT} variation (Task 3). The continuous data collection in Tasks 2 and 3 provided a large number of data points for ANIO computations. Therefore, we sampled the data with various rates to investigate the effect of sample size on the ANIO coefficients. First, the minimum length among all of the data sets in Tasks 2 and 3 was found. The maximal sampling rate corresponded to accepting every tenth data point of the original sampling rate of 100 Hz. Further, we re-sampled the data increasing the interval between successive accepted points by 20

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data points, 40 data points, and 60 data points. The smallest number of data points within a set used for ANIO was 100 (for 60 data point intervals). The ANIO procedure (see later) was applied to each set of data points to define cost functions. The magnitudes of the quadratic coefficients in the reconstructed cost functions (see below) were the same across these analyses. For the rest of the analysis the maximum sampling interval was used resulting in 100-120 data points per set across all subjects and tasks.

Computation of the objective function

The force component normal to the digit-sensor contact interface (F_i^n) of each of the four fingers was used to compute the objective function (Terekhov et al. 2010; Terekhov and Zatsiorsky 2011). The ANIO problem is to compute an objective function $gi(F_i^n)$ such that the fingertip force data are obtained by minimization of *g* under two external constraints: the prescribed F_G, and the required pronation-supination moment to maintain the vertical orientation of the handle. Thus, the ANIO procedure assumes that fingertip normal forces are generated by:

$$\underset{F^n}{argmin} J = \sum_{i=1}^{4} g_i(F_i^n) \quad (1)$$

$$F_1^n + F_2^n + F_3^n + F_4^n = \alpha F_{GM} \quad (2)$$

$$r_1 F_1^n + r_2 F_2^n + r_3 F_3^n + r_4 F_4^n = M_{ext} \quad (3)$$

where $F^n = [F_1^n, F_2^n, F_3^n, F_4^n]^T$ is the vector of normal finger forces ($F_i^n \geq 0, i = 1, \ldots, 4$); the numbers 1 to 4 stand for the index, middle, ring, and little finger, respectively, g_i is an arbitrary continuously differentiable function (g_i belongs to C^n with $n \geq 1$ in the feasible region), F_{GM} is obtained from the baseline trials (See Experimental Procedures), and α is a scalar constant; $r = [r_1, r_2, r_3, r_4]^T$ is the vector of moment arms equal to $[0.45, 0.15, -0.15, -0.45]^T$ in our experiment, where the negative sign indicates clockwise moment (supination). In matrix form:

$$CF^n = b \quad (4)$$

where,

$$C = \begin{bmatrix} 1\ 1\ 1\ 1 \\ r_1 r_2 r_3 r_4 \end{bmatrix} \quad (5)$$

$$b = \begin{bmatrix} \alpha F_{GM} \\ M_{ext} \end{bmatrix} \quad (6)$$

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There are three steps involved in solving the inverse optimization problem. The first two steps are verifications of essential conditions on the data for the ANIO procedure to be applicable. Thus, first we verified that the problem was not "splittable" (Terekhov et al. 2010) for all tasks. A splittable optimization problem can be divided to smaller optimization problems and solved independently. All tasks passed this test, and these results are not presented. Second, since earlier studies with the ANIO method showed that if the conditions on the problem and the data are satisfied and the experimental data are distributed in a plane then the unknown cost function must be quadratic (Martin et al. 2013; Terekhov et al. 2010). Moreover, in the previous studies involving ANIO, the data had planar distribution (e.g. Niu et al. 2012a,b). Therefore, we verified that the data could be fitted with a 2D hyperplane in the four-dimensional space of fingertip normal forces by applying principal component analysis (PCA). The first two principle components explained over 80% of the variance in the fingertip normal forces for all tasks and subjects (see Results), indicating that the data distributions were indeed close to planar.

The third step is computing the coefficients of the objective function. Since the data had approximately planar distributions, according to the ANIO method, the cost function should be searched within the class of second-order polynomials:

$$J^a = \frac{1}{2}\sum_{i=1}^{4} k_i (F_i^n)^2 + \sum_{i=1}^{4} w_i (F_i^n) \qquad (7)$$

where, J^a is the objective function reconstructed from the data, k_i is the i^{th} quadratic term coefficient, and w_i is the i^{th} linear term coefficient. Across hand conditions, these indices refer to different fingers. In the unimanual condition, 1, 2, 3, and 4 refer to the index, middle, ring, and little finger, respectively. In the bimanual conditions, the same numbers refer to the right-index, right-middle, left-index, and left-middle fingers, respectively. Equation 8 shows the Lagrange principle written for the problem $\langle J^a, C\rangle$ in matrix form.

$$\check{C} J^{a'} = 0 \qquad (8)$$

where,

$$\check{C} = I - C^T (CC^T)^{-1} C \qquad (9)$$

$\check{C}$ is a matrix of rank 2, and $J^{a'}$ is a vector consisting of partial derivatives of J^a (gradient vector). Substituting equation 7 in 8 gives the plane of optimal solutions:

$$\check{C} K F^n + \check{C} w = 0 \qquad (10)$$

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where K is the diagonal matrix of quadratic coefficients, and w is the vector of linear coefficients. Rank of $\check{C}$ is 2; therefore, equation 9 defines a plane in the four-dimensional space. ANIO finds the coefficients by minimizing the dihedral angle between the optimal plane defined by equation 10 and experimental plane determined by the first two PCs (see Appendix in Martin et al. 2013). The objective functions were constructed for all three tasks and for each participant separately. The "fmincon" function ("active-set" algorithm) from Matlab optimization toolbox was used to minimize the dihedral angle. Since the cost function can be reconstructed only up to multiplying it by a positive scalar constant, the coefficients have to be normalized. We used normalization by the square root of the sum of squared quadratic coefficients in consistence with (Terekhov and Zatsiorsky 2011; Martin et al. 2013).

Validity of objective function

We used two measures to validate the computed objective function. First, all quadratic terms had to be positive; otherwise, the quadratic function would be non-convex and had a saddle point. We rejected all the cases for which one or more of the quadratic coefficients were negative (across all subject, 13 cases in the bimanual condition across the three tasks, and 3 cases in the unimanual condition – one in each test).

The minimal dihedral angle (D-angle) was the second measure. It determined the goodness-of-fit between the optimal plane and the plane of experimental data. In earlier studies, the D-angle for young, healthy subjects was less than 5° (Niu et al. 2012a,b; Martin et al. 2013).

Statistical analysis

A three-way, analysis of variance (ANOVA) with repeated measures was conducted to evaluate the null-hypothesis that there was no significant change in the quadratic coefficients of the approximated objective function across different *Tasks* (three different methods for data collection), *Hand Conditions* (unimanual and bimanual) and *Finger* (index, middle, ring, and little). As all coefficients were bounded between [0 1], the data were z-transformed before statistical analysis. Significant effects of ANOVA were further explored using pairwise contrasts. Since we had missing data points (cases when an ANIO solution was rejected because of at least one negative second-order coefficient), a mixed-linear model in SPSS was used.

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A non-parametric Wilcoxon signed-rank test was performed on the number of rejected cases for each hand condition to test whether there was significant difference in applicability of ANIO to the unimanual vs. bimanual tasks. The critical p-value was set at 0.05.

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Results

Verifying the planarity of data

Principal component analysis (PCA) was used to verify planarity of the experimental data. The percentage of variance described by the two first PC vectors (%PC), was obtained for each participant in each of the three tasks and both hand conditions (Figure 3, top panel). The percentage of variance described by a plane for the unimanual and bimanual tasks was (84.92±1.61 and 86.28±1.63), (86.21±1.34 and 88.39±2.31), and (81.66±1.42 and 85.9±1.82) for tasks 1, 2, and 3, respectively. A two-way, repeated measures ANOVA on %PC with the factors *Hand-condition* (2 levels) and *Task* (3 levels) showed no significant effects ($p > 0.35$). Hence, we conclude that the data distributions were similarly planar in both hand conditions and across all tasks.

<FIGURE 3 ABOUT HERE>

Cases when ANIO failed

Sometimes, ANIO failed to find a quadratic objective function with all positive quadratic coefficients. Across all unimanual tasks, three objective functions were rejected out of 27, one from each of the three tasks. In contrast, across all bimanual tasks, 13 objective functions were rejected out of 27. A non-parametric Wilcoxon signed-rank test was used to compare the numbers of rejected objective function between the two tasks. The results confirmed that the number of rejected cases in the bimanual tasks was significantly larger than in the unimanual tasks ($p < 0.05$). Further, we analyzed only the acceptable objective functions, i.e., those with all-positive sets of quadratic coefficients.

Coefficients of the objective functions

We applied ANIO to the experimental data sets obtained from the unimanual and bimanual tasks, and estimated the objective function for each subject separately. The quadratic and linear coefficients are shown for each test and hand condition in Table 1.

<FIGURE 3 ABOUT HERE>

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There were no significant differences in the second-order coefficients between the two conditions (unimanual and bimanual), across the three tasks, and across the four fingers. A 3-way repeated-measures ANOVA showed only a significant *Finger* × *Hand-condition* interaction effect ($p < 0.01$). Pairwise contrasts showed several significant differences but none of those were related to our hypotheses. No other effects were seen ($p > 0.1$).

The cost functions were used to compute optimal solutions for the same values of task constraints as those used in the ANIO for each subject separately. This was done only for cases when ANIO was successful in computing a cost function. The dihedral angle (D-angle) between the plane of actual data and the plane of optimal solutions was much larger for the two-hand tasks (Figure 4). The smallest values of the D-angle were observed in Test 1 with discrete trials performed by one hand. A two-way ANOVA, *Test* (3 levels) × *Hand-condition* (2 levels) was used to analyze the D-angle values. There was a significant *Hand-condition* effect [$F_{(1,37)} = 12.31$, $p < 0.01$] confirming that the average D-angle values were higher in the bimanual condition, without other effects ($p > 0.1$).

<FIGURE 4 ABOUT HERE>

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Discussion

Both hypotheses formulated in the Introduction have been confirmed in the study. The first hypothesis was that discrete trials with fixed constraints (as in all earlier studies) and trials with continuously changing constraints would be equally capable of producing data sets for ANIO. We observed that the three tasks used in this study produced data to which ANIO could be applied with equal success. The data showed about equal indices of planarity across the tasks (percent of variance accounted for by the first two PCs, Fig. 3). While the coefficients in the cost functions showed large variability across the tasks and subjects, they showed no significant test dependence. The D-angle showed a tendency towards higher values for the tasks with continuous changes in one of the task constraints (Fig. 4), but this tendency was not statistically significant. Our second hypothesis was that two-hand prehensile tasks would be less successful in reconstructing cost functions with ANIO compared to similar one-hand tasks. Indeed, bimanual tasks were more likely to fail in ANIO as reflected by the significantly larger number of cases when ANIO did not lead to a stable solution, i.e., at least one second-order coefficient was negative. In addition, even in cases when ANIO succeeded in computing a cost function, the D-angle was significantly larger (worse goodness-of-fit) for the bimanual tasks.

Implications for the control of bimanual actions

A number of studies have suggested that there is a leading hand in two-hand tasks (Kelso et al. 1979; Le and Niemeier 2013; Wong et al. 2014). This may partly be due to the hand dominance phenomenon and depend on the type of task. Indeed, humans prefer to use the dominant hand for fast components of actions (e.g., moving the hammer) and the non-dominant hand for steady-state components (e.g., holding the nail). These observations have been formalized as the dynamical dominance hypothesis (Sainburg 2005) and supported in several studies exploring stability of actions by the dominant and non-dominant hand using the framework of the uncontrolled manifold hypothesis (Scholz and Schöner 1999). The dominant hand showed an advantage in processes of preparation to a quick action (Zhang et al. 2006), while the non-dominant hand had an advantage in steady-state tasks (Park et al. 2012; Jo et al. 2015).

Our task can be viewed as a steady-state one. It involved only slow adjustments in the grip force and total moment of force while holding the handle vertically. Hence, one could expect that

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the non-dominant hand would be the leading one in this task. This assumption is supported by recent studies of movement kinematics, while their application to kinetic tasks has been questioned (Diedrichsen 2007; Dounskaia et al. 2010). In our opinion, force tasks and kinematic tasks are both controlled by shifts in referent coordinates for the effectors and differ primarily in the external loading conditions (cf. Feldman 1986, 2015; Latash 2010). Hence, we think that the idea of a leading hand can be applied to two-hand kinetic tasks as supported by a recent study of two-hand and two-person accurate force production (Solnik et al. 2015). Under this assumption, our main results –the bimanual tasks failed more frequently and had poorer goodness-of-fit indices – suggest that mechanisms reflected by ANIO are limited to neural circuitry involved in the control of one of the hands (possibly the non-dominant hand) and cannot involve digits of both hands. This hypothesis remains speculative and may be studied in future experiments with more than two fingers per hand.

Speaking about neurophysiological mechanisms, both large hemispheres are involved in the control of one-hand tasks, while their relative involvement may depend on the task nature. Studies of stroke survivors have shown that an injury to a hemisphere leads to an impairment in both contralesional and ipsilesional hands, and the type of the impairment depends on whether the injured hemisphere is dominant or non-dominant (Winstein et al. 1999; Haaland et al. 2004 Mani et al. 2014). In healthy persons, however, both hemispheres are involved in one-hand actions (reviewed in Mutha et al. 2012). Our results may reflect failure of the "leading hemisphere" to adhere to a single rule of optimality in two-hand tasks or they may reflect the inability of the two hemispheres to cooperate in organizing optimal control of the two hands.

The relative failure of ANIO in two-hand tasks may also be a reflection of the much larger range of solutions compatible with the task constraints explored by the subjects in such tasks compared to one-hand tasks. Studies of two-hand accurate force production during pressing tasks have shown a broader range of solutions used by the subjects in such tasks compared to similar tasks performed by one hand (Gorniak et al. 2007a,b). When the two hands belong to different persons, the range of solutions becomes even larger (Solnik et al. 2015). Assuming that there is an optimal solution for each of those tasks, the larger range of solutions means that in two-hand tasks subjects deviated from those optimal solutions more. This could be the reason for ANIO being less able to find an acceptable cost function and for the cost functions to describe the data less accurately compared to the one-hand condition (as shown in our experiments).

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ANIO could also fail if the two hands were controlled independently in our bimanual tasks. We view this as unlikely because independent hand control would likely lead to major violations of task constraints, which we did not observe. Indeed, the two-hand tasks were performed with at least the same, if not higher, accuracy compared to the one-hand tasks. This could be related to the fact that the bimanual tasks were performed with the strongest and most accurately controlled fingers of both hands (index and middle fingers), while the unimanual tasks involved the less powerful and accurate ring and little fingers (Shinohara et al. 2003; Gorniak et al. 2008). We did not study finger force inter-trial covariation, which would provide a more definitive answer. Such an experiment would require multiple trials at each given condition, and our experimental sessions were already rather long. Note that earlier studies by Gorniak and her colleagues (2007, 2009) provided evidence for strong between-hand covariation of forces in both pressing and prehensile tasks.

A fundamental assumption behind the ANIO method is that the cost function for a set of elements can be represented as a linear combination of individual cost functions for each element. For prehensile tasks, we assume that the cost function explaining the sharing among individual fingers is the sum of individual cost functions for each finger as described by Equation 1. This assumption of additivity is based on an intuitive idea that there is a level of control within the CNS that defines the involvement of individual fingers. For bimanual tasks, however, it is reasonable to assume that the control involves several hierarchical levels, such as 1) sharing the task between the left and right hands; 2) sharing each hand's action between the thumb and the opposing virtual finger; and 3) sharing the virtual finger action among the actual fingers (Arbib et al. 1985; Gorniak et al. 2007a; Zatsiorsky and Latash 2008). It is possible that the additivity assumption is violated at one or more of the mentioned levels; i.e., that the CNS combines cost functions for the left and right hands differently from how it combines cost functions for the fingers of the same hand. This suggests that the relative failure of ANIO in bi-manual tasks could be due to violation of the additivity assumption, essential for veridical identification of the cost function (Terekhov and Zatsiorsky 2011).

We did not study possible differences between the dominant and non-dominant hand in the ability of ANIO to compute cost functions because of practical reasons: Our testing sessions already challenged patience of the subjects. This remains a drawback and would be an important study to run in future.

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Whatever the reason is, two-hand tasks are not following a single additive cost function as well as one-hand tasks do. They either fail completely in a high percentage of cases (close to 50%) or result in very large D-angle values. These observations are comparable to failure of ANIO to account for the joint moment distribution patterns in hand force production tasks (Xu et al. 2012). The two studies, however, are rather different: The study by Xu and co-authors involved a serial chain within one limb, while our current study involved a parallel chain formed by fingers of both hands. Whether there is a general rule of ANIO applicability to motor tasks performed by humans remains an open question.

ANIO with continuously changing constraints

A practical limitation of using ANIO has been the requirement to have many data points covering a wide range of constraint values (Terekhov et al. 2010; Terekhov and Zatsiorsky 2011). This requirement is hard to meet in clinical studies because of both time constraints and quick fatigue, which is typical of various neurological patients. So far, only one study applied ANIO to data collected in patients (with early-stage Parkinson's disease; Park et al. 2013). The study showed that those patients were similar to healthy controls in the ability of ANIO to compute cost functions, but the goodness-of-fit was significantly compromised in the patients (reflected in high D-angle values).

Our study shows that continuously changing constraints can be used to collect data. This makes the study potentially important for future clinical applications. Indeed, a single trial with varying constraint (grip force or external torque in our study) allows collecting a very large number of data points. Using all of those points would probably be a questionable strategy from the point of view of statistics given that consecutive points are non-independent. But even if the points are sampled at reasonable time intervals, this still allows obtaining dozens of data points in a single trial. So, a handful of trials might be sufficient to obtain enough data points for ANIO. We hope that this extension of the method will facilitate its application to clinical studies.

What does ANIO failure mean?

ANIO failed in our study in both two-hand and one-hand conditions, although failures in the one-hand tasks were rare. There may be a number of reasons why ANIO happens to be unable to compute an acceptable cost function (with all-positive coefficients at the second-order terms)

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or leads to poor fit to the original data following direct optimization (large D-angle values). These range from quality of the data to combining data that should not be combined in an analysis to dealing with a system that uses an optimization principle that violates ANIO assumptions.

Arguably, the most obvious reason for ANIO to work poorly would be irreproducible behavior of subjects. In other words, subjects may change their strategies across trials and use different cost functions in different trials. This is always a possibility, in particular during long-lasting experimental sessions. Even if the subjects do not report fatigue, they may become bored and start experimenting with different ways to perform tasks without being aware of this. Combining such data into a set and using ANIO would likely lead to poor results, either lack of a stable solution or high D-angle.

It is possible that the subjects are trying their best to perform consistently but the nature of the study leads to different cost functions for different fragments of the tasks. For example, phenomena of hysteresis have been reported over many studies of motor behavior; in particular, subjects grip objects differently depending on the direction of slow change in the object's weight or external torque (Sun et al. 2011a,b). In our study, similar combinations of constraints could be achieved with different rates of change of the constraints, zero, positive, or negative. While we have not observed any significant effects of factors that could potentially lead to hysteresis effects (e.g., differences across the three tasks), one cannot rule out that such effects played a role. On the other hand, if such factors played an important role, we would expect their effects to be equally pronounced in one-hand and two-hand tasks, which was not the case.

ANIO can also fail if one of its main assumptions is violated. For example, if the subjects are using non-additive cost function or if the function varies over different combinations of constraints. This would be a likely factor if ANIO failed across all subjects and tasks. This was indeed the case in the only earlier study reporting failure of ANIO (Xu et al. 2011). In our study, however, some subjects in some tasks produced data sets in the two-hand condition leading to successful application of ANIO and low D-angle values comparable to those in the one-hand condition. This suggests that the main ANIO assumptions were probably not violated, and the reason for the relatively poor performance of ANIO in two-hand tasks was one of the previously mentioned factors.

To conclude, we show that ANIO can be used in tasks with slowly changing constraints making it an attractive tool to study optimality of performance in special populations. We also

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show that ANIO can fail in multi-finger tasks, likely due to irreproducible behavior across trials, more likely to happen in bimanual tasks compared to unimanual tasks.

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Table 1. Quadratic coefficients for each test and hand condition.

	Test 1		Test 2		Test 3	
	Unimanual	Bimanual	Unimanual	Bimanual	Unimanual	Bimanual
$\boldsymbol{k_1}$	0.347±0.123	0.337±0.168	0.380±0.134	0.395±0.161	0.401±0.142	0.271±0.135
$\boldsymbol{k_2}$	0.164±0.058	0.226±0.113	0.057±0.020	0.412±0.168	0.106±0.037	0.261±0.131
$\boldsymbol{k_3}$	0.155±0.055	0.195±0.097	0.140±0.050	0.361±0.147	0.135±0.048	0.298±0.149
$\boldsymbol{k_4}$	0.271±0.096	0.277±0.138	0.294±0.104	0.113±0.046	0.367±0.130	0.078±0.039

Across-subjects means ± standard errors are shown. Coefficients for quadratic terms are shown with k_i (i=1,…,4). Moreover, they were normalized such that the square root of the sum of all four coefficient squared was set at unity. In unimanual condition indices from 1 to 4 stands for index, middle, ring, and little finger, respectively. However, in bimanual condition first two indices refer to index and middle fingers of right hand, and the last two correspond to index and middle fingers from left hand.

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Figure Captions

Figure 1: (A) The handle with the force/moment sensors and the inverted-T-shaped slider mechanism used in the experiment; (B) The finger placement in the unimanual task. (C) The experiment setup and hand positions during bimanual tasks. (D) A close-up of a typical finger configuration for the bimanual task.

Figure 2: Visual feedback on grip force in Task 1 (a), Task 2 (b), and Task 3 (c). The green dashed line is the task template on grip force and the black line is an example of grip force profile produced by subjects. The red vertical dashed line shows when the subjects were required to match the template.

Figure 3: Percentage of variance described by the first two principal components. Averaged across participants values with standard error bars are presented.

Figure 4: The dihedral angle (D-angle) for the three tasks and two hand conditions. Averages across participants with standard error bars are shown.

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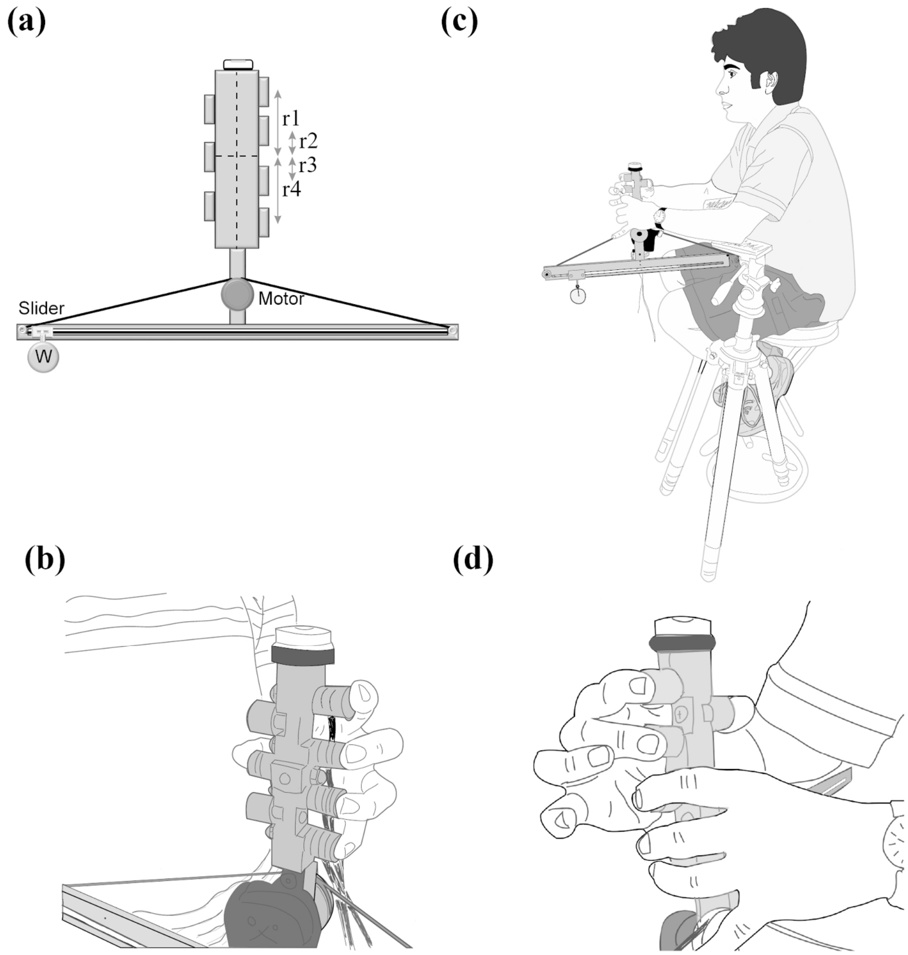

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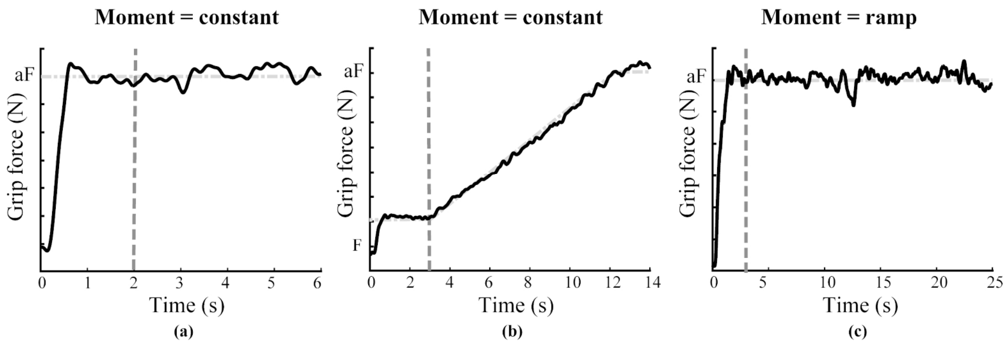

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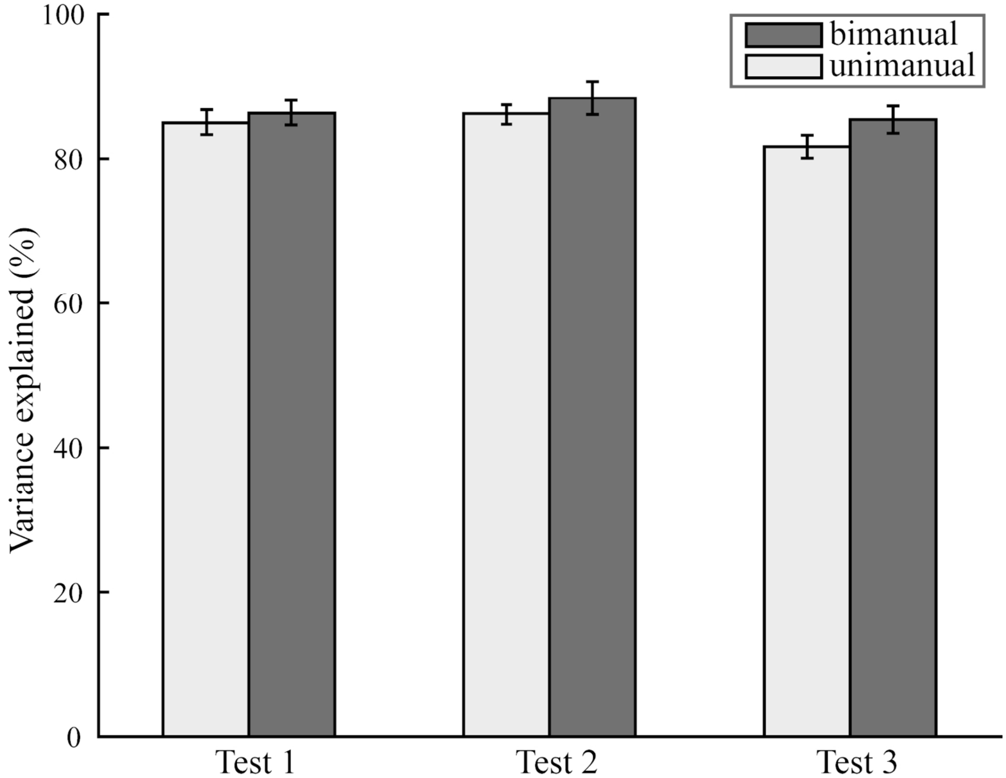

Figure 3: Percentage of variance described by the first two principal components. Averaged across participants values with standard error bars are presented.
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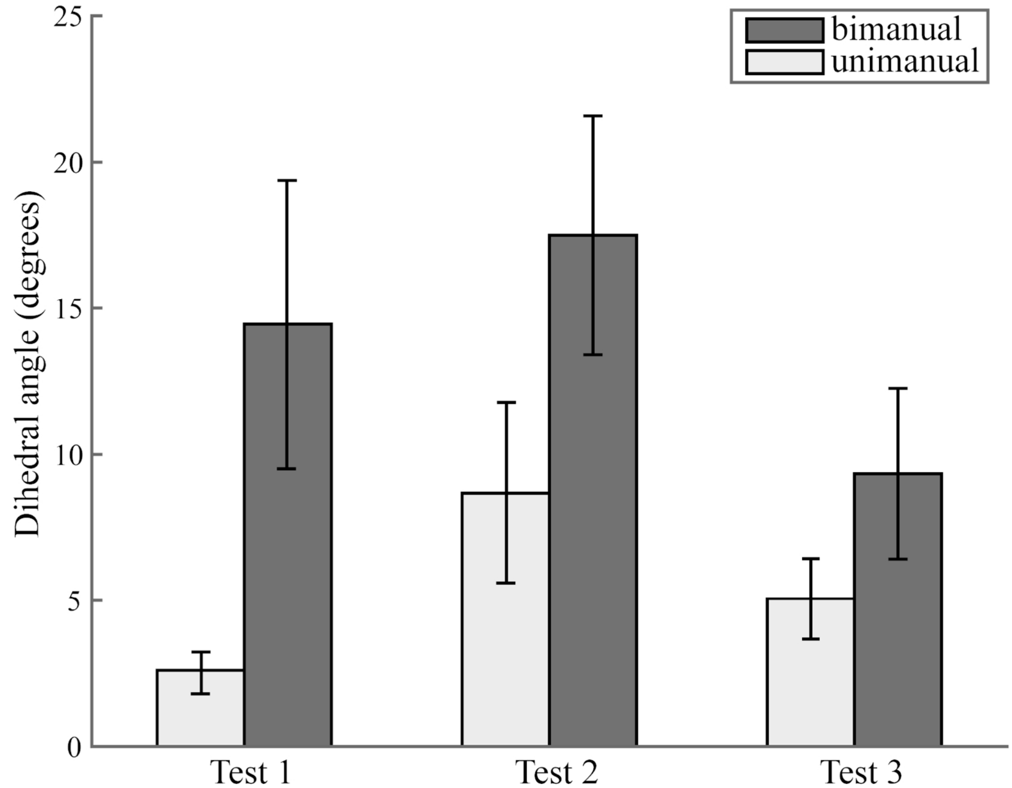

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139x111mm (300 x 300 DPI)